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Intelligent fault diagnosis for power distribution system-comparative studies

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ABSTRACT

Short circuit is one of the most popular types of permanent fault in power distribution system. Thus, fast and accuracy diagnosis of short circuit failure is very important so that the power system works more effectively. In this paper, a newly enhanced support vector machine (SVM) classifier has been investigated to identify ten short-circuit fault types, including single line-to-ground faults (XG, YG, ZG), line-to-line faults (XY, XZ, YZ), double line-to-ground faults (XYG, XZG, YZG) and three-line faults (XYZ). The performance of this enhanced SVM model has been improved by using three different versions of particle swarm optimization (PSO), namely: classical PSO (C-PSO), time varying acceleration coefficients PSO (T-PSO) and constriction factor PSO (K-PSO). Further, utilizing pseudo-random binary sequence (PRBS)-based time domain reflectometry (TDR) method allows to obtain a reliable dataset for SVM classifier. The experimental results performed on a two-branch distribution line show the most optimal variant of PSO for short fault diagnosis.

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1. INTRODUCTION

Short circuit fault is known as a common undesirable phenomenon which may serious damage equipment and interrupt the electrical power supply. Thus, it is necessary to monitor this fault carefully at first, and then clear it fastest as possible in order to enhance the reliability as well as power quality [1], [2]. Recently, many methods have been proposed to recognize fault types in distribution line. The authors introduced a fault diagnosis method based on the measurement of voltage and current using an intelligent electronic device (IED) [3]. Meanwhile, utilizing a cross-correlation rate (CCR) between reflected and incident wave allows to identify the status of distribution systems with simple topology [4]. To evaluate error status in more special feeds, artificial neuron network (ANN)-based method has applied to enhance the reliability of systems [5], [6]. Among of them, time domain reflectometry (TDR) is known as a promising tool for detecting the faulty lines because of simple implementation and few adjusted parameters [7]-[9]. The main drawback of this method is the attenuation of signal along the line, thus it is essential to use binary random pseudo sequence (PRBS) excitation [10].

Nevertheless, the reflected signal analysis methods are not easy to deploy on multi-branch lines due to synthesis of multiple response waves and hence it is often combined with intelligent diagnostic methods, such as ANN [11], [12] or support vector machine (SVM) [13], [14]. Because of wider generalization and

global optimization capability, SVM demonstrates the superiority as compare different intelligent methods in determining the fault type [15]. To enhance the efficiency of SVM, there are many methods, including grid search method (GSM) [16], genetic algorithm (GA) [17], [18] that allow to increase the classification precision. The main disadvantage of these methods is easy to fall into local optimization area.

In this paper, the performance of SVM is improved by using three variants of particle swarm optimization (PSO), including classical PSO (C-PSO), T-PSO, and K-PSO for classifying various types of faults in power distribution networks. For this purpose of classification, the reflected signals obtained from TDR analysis in MATLAB/Simulink environment are used to construct a database. Further, selection of training and testing dataset from a given dataset has been made in two ways: i) randomly and kept fixed at each iteration and ii) randomly and continue random selection at each iteration. The training and testing dataset are separated from this dataset with the ratios of 3:1 and 4:1.

2. MATERIALS

2.1. Time-domain reflectometry (TDR)

TDR is utilized to collect the effects caused by faults occurred in any network. The characteristic of electrical fault is evaluated based on reflected signals after injecting a pulse beam into a line or a cable [19]. To identify the fault location and type, we simulate a distribution line as an equivalent electrical circuit in Figure 1.

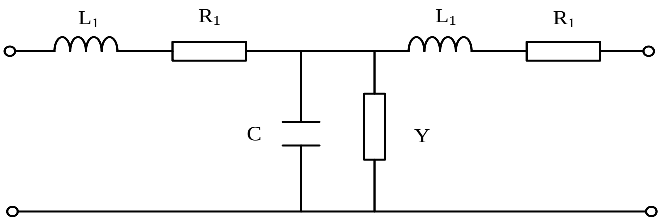

Figure 1. Approximate equivalent modeling of power distribution line

The model characteristic impedance Z_0 and the propagation coefficient σ for the equivalent circuit in Figure 1 are given by:

$$Z = \sqrt{\frac{(R_1 + j\omega L_1)}{(Y + j\omega C)}} \tag{1}$$

$$\sigma = \sqrt{(R_1 + j\omega L_1)(Y + j\omega C)} = x + jy \tag{2}$$

$$x = \sqrt{\frac{1}{2}\left[\sqrt{(R_1^2 + w^2 L_1^2)(y^2 + w^2 C^2) + (R_1 y - w^2 L_1 C)}\right]} \tag{3}$$

$$y = \sqrt{\frac{1}{2}\left[\sqrt{(R_1^2 + w^2 L_1^2)(Y^2 + w^2 C^2) - (R_1 y - w^2 L_1 C)}\right]} \tag{4}$$

where x is known as the attenuation coefficient and y is the phase change coefficient.

The cross-correlation rate (CCR) of the response and incoming signal is calculated as follows: incident wave given by (5) are used as input vectors of SVM for the purpose of fault classification.

$$C_{xy}(k) = \frac{1}{L}\sum_{i=1}^{L} x(i)y(i+k) \tag{5}$$

C_{xy}(k) is used as input vectors of SVM.

2.2. Support vector machine (SVM)

SVM works based on statistical learning theory (SLT) to satisfy structural risk minimisation (SRM), which was first proposed by Vapnik in 1995 [20]. SVM is widely used in two main areas: classification and regression, in which the classification problem is considered as a two-class data recognition without change of high generality.

In two-class problem, suppose we have a training dataset:

$D=\{(p_1, q_1), (p_2,q_2),\ldots,(p_n,q_n)\}$

$p_i \in R_n$, $q_i \in (-1, +1)$, where p_i is a data vector and q_i are a class label.

The binary classification problem can be done finding the minimum value of this following function:

Minimize:

$$\frac{1}{2}||\omega||_2^2 + H\sum_{i=1}^{n}\beta_i \tag{6}$$

Under the constraints:

$$q_i(\omega \cdot p_i) + \alpha \geq 1 - \beta_i, \beta_i \geq 0, i = 1, \ldots, m \tag{7}$$

where w is the weight vector, H is the adjusted factor or γ penalty parameter; and α is a scalar. The problem is computationally solved using the solution of its dual form:

$$max_\gamma\ F(\gamma) = \sum_{i=1}^{n}\gamma_i - \frac{1}{2}\sum_{i,j=1}^{n}\gamma_i\gamma_j q_i q_j K(p_i, p_j). \tag{8}$$

where n is the number of support vector, γ_i the Lagrangian multipliers, and the kernel function $K(p_i,q_i)$ is given by (9):

$$K(x,y) = exp(-\delta\|x-y\|^2) \tag{9}$$

where δ is the kernel function parameter.

3. PARTICLE SWARM OPTIMIZATION (PSO)

PSO is a swarm intelligence-based optimization technique that works based on behavious inspiration of fish swarm or birth school to find the most optimum position. PSO is superior to other optimization algorithms because of the memory ability of personal experience (L_{best}) and overall experience (S_{best}) [21]-[23]. Given a swarm of size n flying in the space of d dimension, in which each particle moves with the velocity of V:

$$Pi,j = [Pi,1, Pi,2, \ldots, Pi,d]T$$
$$Vi,j = [Vi,1, Vi,2, \ldots, Vi,d]T,$$
$$i \in (1,n), j \in (1,d)$$

3.1. Classical PSO

As mentioned above, each individual will update the new position based on experience of itself and the best particle in swarm. This can be described by (10) and (11):

$$V_{i,j}^{p+1} = \omega \times V_{i,j}^{p} + c_1 r_1(L_{best}{}_{i,j}^{p} - P_{i,j}^{p}) + c_2 r_2(G_{best}{}_{j}^{p} - P_{i,j}^{p}) \tag{10}$$

$$P_{i,j}^{p+1} = P_{i,j}^{p} + V_{i,j}^{p+1} \tag{11}$$

In (10), c_1 and c_2 are acceleration values, r_1 and r_2 are random parameters in range of [0, 1], ω is the inertia weight, $L_{besti,j}^p$ demonstrates the best j^{th} element j^{th} of i^{th} particle, while $G_{besti,j}^p$ demonstrates the j^{th} element of the best particle in a swarm upto interation p.

Each individual is initialized by the position of L_{best}, in which the best particle position in swarm is known as G_{best}. After interation p, L_{best} and G_{best} of each individual are updated as follows,
At iteration k:

$$If\ f\left(P_i{}^{p+1}\right) < f\left(L_{best}{}_i{}^{p}\right)\ then\ \mathrm{L}_{best}{}_i{}^{p+1} = P_i{}^{p+1} else\ L_{best}{}_i{}^{p+1} = L_{best}{}_i{}^{p} \tag{12}$$

$$If\ f\left(P_i{}^{p+1}\right) < f\left(G_{best}{}^{p}\right)\ then\ G_{best}{}^{p} = \mathrm{P}_i{}^{p+1} else\ G_{best}{}^{p+1} = G_{best}{}^{p} \tag{13}$$

where f(·) is the objective function. The updating process is repeated until a stop condition is reached, such as a pre-specified number of iterations is met. The obtained results (G_{best}^p and $f(G_{best}^p)$) are knowns as solution of PSO algorithm.

3.2. Time varying acceleration coefficients PSO (T-PSO)

In this version of PSO, both the acceleration coefficients (c_1 and c_2) are varied at each iteration. The acceleration coefficient c_1 is decreased whereas acceleration coefficient c_2 increased linearly as iteration proceeds. Time varying acceleration coefficients are (TVAC) expressed as shown in [24],

$$c_1 = c1, min1, max_{1,max} \quad (14)$$

$$c_2 = c2, min2, max_{2,min} \quad (15)$$

in (14), $c_{1,min}$ and $c_{1,max}$ are the minimum and maximum limits of acceleration factor c_1 whereas in (15), $c_{2,min}$ and $c_{2,max}$ are the minimum and maximum limits of acceleration factor c_2.

3.3. Constriction PSO (K-PSO)

In this version of PSO, a new velocity update equation is introduced by removing the traditional inertia weight factor. The velocity update equation considering constriction factor approach PSO (in this work it is called K-PSO) is given as follows; where α, β are the attenuation coefficient and the phase change coefficient, respectively.

$$V_{p,q}^{k+1} = K \times \left[V_{p,q}^k + c_1 r_1 (Pbest_{p,q}^k - X_{p,q}^k) + c_2 r_2 (Gbest_q^k - X_{p,q}^k)\right] \quad (17)$$

In (16), K is known as the constriction factor of PSO which is defined as follows [25],

$$K = \frac{2\kappa}{|2-\varphi-\sqrt{\varphi^2-4\varphi}|} \quad (18)$$

where $\phi = c_1 + c_2$ and κ = [0, 1]; ormally, the value of κ is taken as 1. Once the updated velocity of each particle is obtained using (16) then the position of each particle is updated using (11).

4. VARIANTS OF PSO-BASED SVM FOR FAULT CLASSIFICATION

In this section, PSO and its two variants is proposed to search the optimal parameters of SVM in order to improve classification performance by the following steps:

1) The data obtained by using TDR with PRBS stimulus is divided into the training and testing set.
2) Initialize the parameters of PSO (ω, c_1, c_2)
3) The initial positions and velocities of each individual in swarm are selected by random values
4) Set parameters of SVM model within their ranges
5) Call SVM
6) Evaluate the objective function of each particle: $F_i^p = f\left(P_i^p\right)$
   The best particle position is indexed as v, and hence the experience of itself and the best particle in swarm is chosen by: ${L_{besti}}^p = {P_i}^p$, and ${G_{best}}^p = P_i^p$
7) Set p =1
8) Updating the velocity and position of each particle by (10) and (11)
9) The objective function of each particle is re-evaluated
10) If p < Max than p = p+1 and go to the step 7 else go to the final step
11) The optimum parameters of SVM are knowns as ${G_{best}}^p$

5. SIMULATION RESULTS AND DISCUSSION

Since TDR methods are inherently imprecise, it is necessary to add other supporting techniques in order to achieve reliable results. In this work, the proposed comparative studies of various types of PSO algorithms in obtaining optimum SVM parameters are test on a two-branch distribution model, as given in Figure 2. For this, the data acquisition for data preprocessing is mentioned first.

5.1. Training and testing samples

By using TDR with PRBS excitation, a set of 5600 samples with 12 features for each sample has been generated. These datasets have been categorized into the training and testing dataset in the two following ways;

– Choose the training and testing dataset randomly from the given dataset but kept fixed during the process.
– Choose the training and testing dataset randomly and continue randomly selection during each iteration.

5.2. Results for randomly divided training and testing datasets and are kept fixed during the iteration

In this case, initially, the entire dataset has been divided into training and testing sets randomly and kept fixed during training phase to obtain the optimum SVM parameters. Two different ratios for the division of the entire dataset into the testing and training set have been considered: 1400-4200 and 1120-4480 samples belong to the testing and the training dataset, respectively. The optimum SVM parameters obtained using C-PSO, T-PSO, and K-PSO for fault classifications of a two-lateral radial distribution system in two different sets of dataset division are given in Table 1. Further, results obtained are compared to that obtained in the case of being without any PSO algorithm. The corresponding convergence characteristics of the three algorithms are shown in Figure 3 and Figure 4.

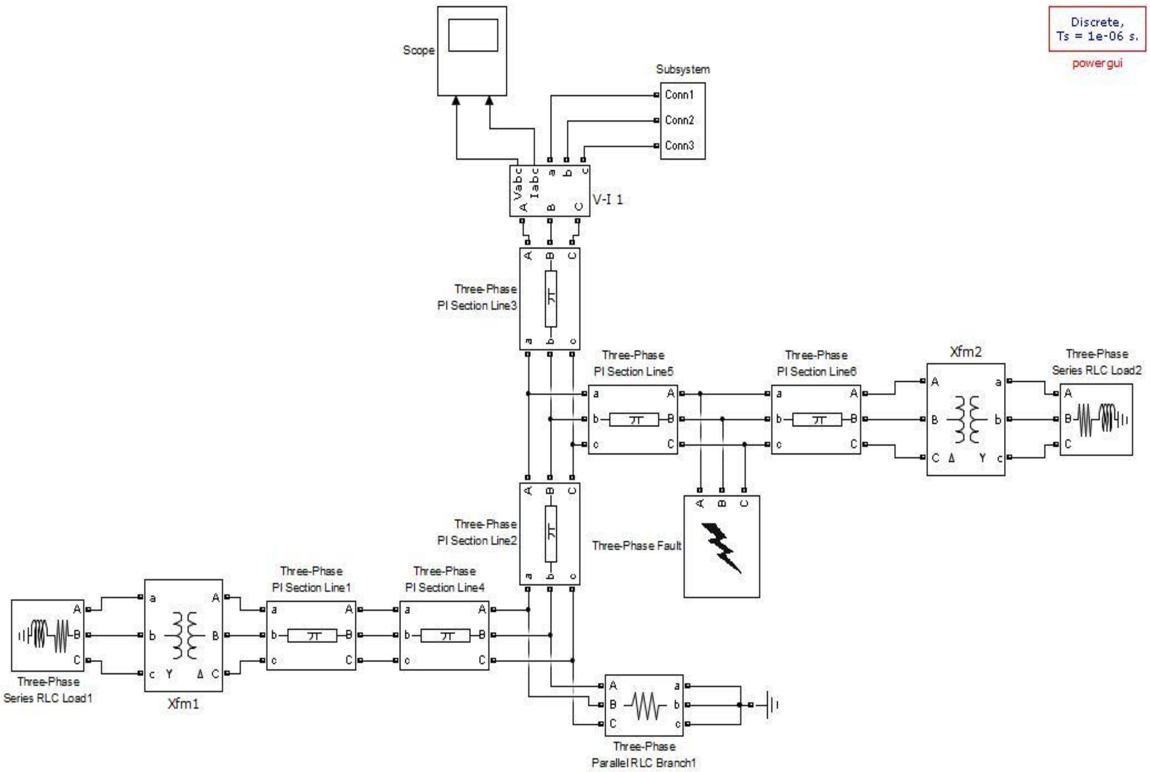

Figure 2. The model of tested distribution system

Table 1. Optimum SVM parameters obtained using various PSO variants considering selection of the training and the testing dataset selected randomly and kept fixed during each iteration

Data pattern Test: Train	SVM	Optimum SVM parameters C	γ	Accuracy (%)	Run time (seconds)
1400: 4200	straight	100	0.33	85.5714	134.8
	C-PSO	337.0326	0.5190	96.7143	90.1
	T-PSO	298.0396	0.4753	96.7143	82.9
	K-PSO	410.6090	0.4321	96.7857	77.8
1120: 4480	straight	100	0.33	85.9821	158.5
	C-PSO	107.1691	1.1022	96.1607	142.8
	T-PSO	206.1728	3.7482	96.8750	112.1
	K-PSO	384.8476	0.6141	96.8750	69.3

From Table 1, it is observed that in the testing and the training data division of 1400 and 4200, K-PSO gives the highest testing accuracy of 96.7857% in 77.8 seconds which is the fastest. The optimum SVM parameters in this case are C=410.6090 and γ=0.4321. From Figure 3, it can be observed that the characteristic of K-PSO is better (lower) than that of the other two algorithms. However, in the training and the testing data division of 1120 and 4480, T-PSO and K-PSO give the highest accuracy of 96.8750%. Here, T-PSO takes 112.1 seconds whereas K-PSO takes only 69.3 seconds which is the fastest among PSO algorithms. The optimum SVM parameters in this case are C=206.1728 and γ=3.7482 by T-PSO and C= 384.8476 and γ=0.6141 by K-PSO. From Figure 4, it can be observed that the characteristics of T-PSO and

K-PSO are better than that of C-PSO whereas the characteristic of K-PSO is the best among the three algorithms. In this data division, K-PSO is the fastest one. From Table 1, it is to be noted that in both types of dataset division, all three PSO algorithms give better accuracy than that obtained by the SVM classifier without PSO algorithm. Further, from Table 1, it is observed that the division of the testing and the training dataset has the impact on accuracy as well as on the speed of convergence. More samples in the training gives better accuracy.

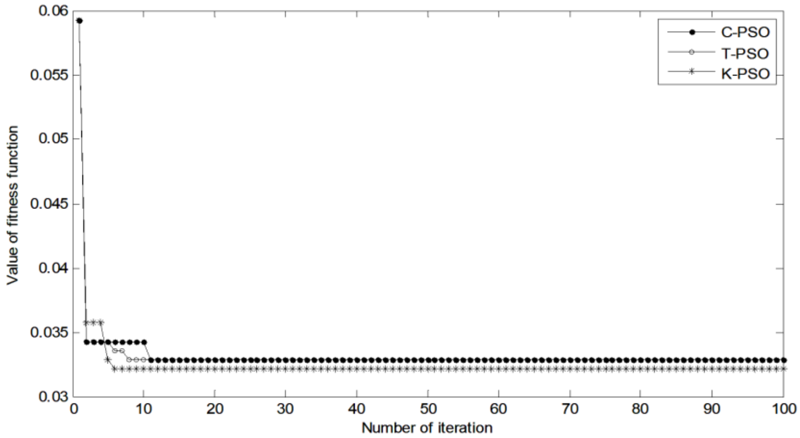

Figure 3. Comparative convergence characteristics of various PSO algorithms for testing: training dataset as 1400: 4200 in initial random selection and kept fixed at each iteration

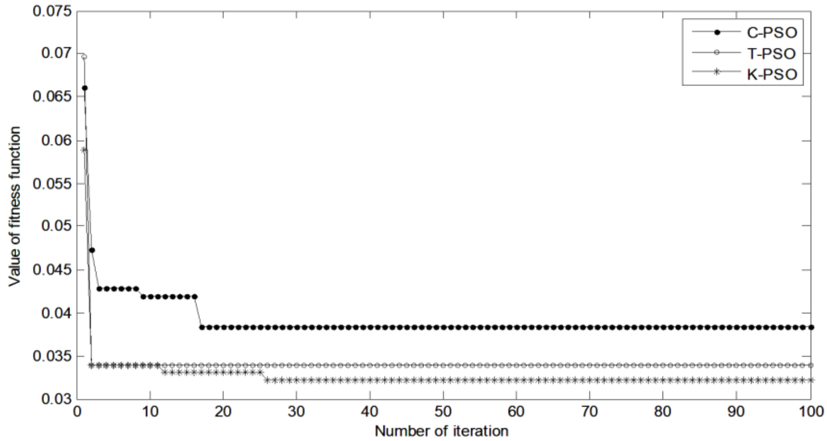

Figure 4. Comparative convergence characteristics of various PSO algorithms for testing: training dataset as 1120: 4480 in initial random selection and kept fixed at each iteration

5.3. Results for randomly divided training and testing datasets and continue dividing randomly during the iteration

In this case, the entire dataset has been divided into training and testing sets randomly and continue dividing randomly during the training to obtain the optimum SVM parameters. As in the previous subsection, two different ratios for the division of the entire dataset into testing and training sets have also been considered in this case.

The optimum SVM parameters obtained using C-PSO, T-PSO and K-PSO for fault classifications of a two-lateral radial distribution system in two different sets of dataset division are given in Table 2. The corresponding convergence characteristics of the three PSO algorithms are shown in Figure 5 and Figure 6. From Table 2, it is observed that in the testing and the training data division of 1400 and 4200, K-PSO gives the highest testing accuracy of 96.3571% in 151.3 seconds. T-PSO is the fastest in this dataset division. From Figure 5, it can be observed that the characteristic of K-PSO is better than that of the other two algorithms. However, in the training and the testing data division of 1120 and 4480, K-PSO gives the highest accuracy of

96.875% in 155.2 seconds which is the fastest. From Figure 6, it can be observed that the characteristic of K-PSO is much better than that of the other two algorithms.

Further, from Table 2, it is observed that the division of the testing and the training dataset has the impact on accuracy as well as on the speed of convergence. From Table 1 and Table 2, it can be concluded that higher samples in the training set gives better accuracy. Although the overall accuracy presented in these two tables is virtually the same, however, the results in the latter one is generalized because of continuing random selection of different sets of the training and the testing samples during training the SVM. Further, K-PSO gives the best among the PSO algorithms in terms of the classification accuracy as well as simulation time taken. Also, from Figures 3 to 6, it can be clearly observed that the convergence characteristic of K-PSO is the best and the convergence characteristic of T-PSO is better than that of C-PSO.

Table 2. Optimum SVM parameters obtained using various PSO variants considering selection of the training and the testing dataset selected randomly and continuing as the same during each iteration

Data pattern Test: Train	SVM	Optimum SVM parameters C	γ	Accuracy (%)	Run time (seconds)
1400: 4200	straight	100	0.33	85.5714	134.8
	C-PSO	909.4291	1.0285	96.2143	147.7
	T-PSO	359.2888	0.5582	96.0714	90.1
	K-PSO	323.2542	1.1171	96.3571	151.3
1120: 4480	straight	100	0.33	85.9821	158.5
	C-PSO	574.5739	1.2078	96.6964	191.3
	T-PSO	196.2483	1.3363	96.6071	237.4
	K-PSO	316.9958	1.3340	96.875	155.2

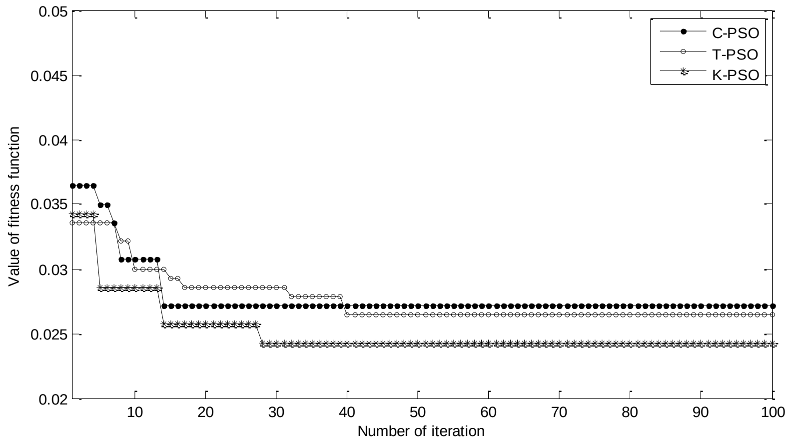

Figure 5. Comparative convergence characteristics of various PSO algorithms for testing: training dataset as 1400: 4200 in randomly selected and continuing as the same at each iteration

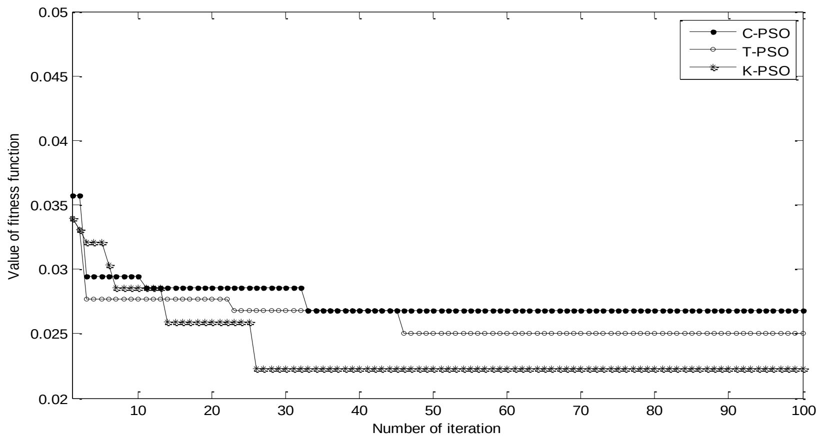

Figure 6. Comparative convergence characteristics of various PSO algorithms for testing: training dataset as 1120: 4480 in randomly selected and continuing as the same at each iteration

6. CONCLUSION

In this paper, variants on particle swarm optimization (PSO) have been purposed to improve the performance of the support vector machine (SVM) classifier in classifying faults in distribution systems. Further enhancement of the proposed method has been provided by the success in generating the necessary fault current dataset by TDR analysis with PRBS excitation. The obtained results show that the performance of SVM is better with the parameters obtained by variants of PSO, in which K-PSO algorithm gives the highest classification accuracy of 96.87%. Further, classification result is generalized while randomly selecting dataset during the training phase of SVM. Also, two different ratios used in dividing the training and testing dataset were considered, which shows that provision of a higher training dataset gives better classification accuracy versus that performed with a lower dataset.

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